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AUTHOR	Yu, Chong Ho
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ABSTRACT

Although quantitative research methodology is widely applied by psychological researchers, there is a common misconception that quantitative research is based on logical positivism. This paper examines the relationship between quantitative research and eight major notions of logical positivism: (1) verification; (2) pro-observation; (3) anti-cause; (4) downplaying explanation; (5) anti-theoretical entities; (6) anti-metaphysics; (7) logical analysis; and (8) frequentist probability. It is argued that the underlying philosophy of modern quantitative research in psychology is in sharp contrast to logical positivism. Putting the labor of an out-dated philosophy into quantitative research may discourage psychological researchers from applying this research approach and may also lead to misguided dispute between quantitative and qualitative researchers. What is needed is to encourage researchers and students to keep an open mind to different methodologies and apply skepticism to examine the philosophical assumptions instead of accepting them unquestioningly. (Contains 1 figure and 75 references.) (Author/SLD)

Misconceived relationships between logical positivism and quantitative research:

An analysis in the framework of Ian Hacking

Chong Ho Yu, Ph.D.

Arizona State University

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Correspondence:

Chong Ho Yu, Ph.D.

Educational Data Communication,

Assessment, Research, and Evaluation

Psychology in Education

302 Payne Hall

Arizona State University

Tempe AZ 85287-0611

Phone: (480)965-3475

Email: alexyu@mainex1.asu.edu

Abstract

Although quantitative research methodology is widely applied by psychological researchers, there is a common misconception that quantitative research is based upon logical positivism. This article examines the relationship between quantitative research and eight major notions of logical positivism: (a) verification (b) pro-observation (c) anti-cause (d) downplaying explanation (e) anti-theoretical entities (f) anti-metaphysics (g) logical analysis and (h) frequentist probability. It is argued that the underlying philosophy of modern quantitative research in psychology is in sharp contrast to logical positivism. Putting the label of an out-dated philosophy onto quantitative research may discourage psychological researchers from applying this research approach, and also lead to misguided dispute between quantitative and qualitative researchers. What is needed is to encourage researchers and students to keep an open mind to different methodologies and apply skepticism to examine the philosophical assumptions instead of unquestioning acceptance.

Misconceived relationships between logical positivism and quantitative research: An analysis in the framework of Ian Hacking

Introduction

Feldman (1998) observed that while positivism has been universally rejected by philosophers of science over the past fifty years, current textbooks on psychological research still either label quantitative research as positivist or cover quantitative research within a positivist frame of reference. Further, in many texts comparing qualitative and quantitative research, the attributes of the latter are often misidentified with labels that imply value judgment. The following are some examples: particularistic (quantitative) vs. holistic (qualitative) emphasis, outcome-oriented (quantitative) vs. process-oriented (qualitative), fixed (quantitative) vs. emergent categories (qualitative), and static (quantitative) vs. fluid reality (qualitative) (Huysamen, 1997), mechanical (quantitative) vs. creative (qualitative), formulaic (quantitative) vs. interpretive (qualitative) (Howe, 1988).

However, these comparisons are grounded on the misunderstood relationship between quantitative research and the positivist or logical positivist paradigms. This article discusses the core ideas of positivism and points out that the preceding perceived connection is mistaken. One of the sources of the misunderstanding can be traced back to the narrow definition of quantitative research. Quantitative research is commonly viewed as Fisherian hypothesis testing. In this article, quantitative methods include all numeric-based computational methodologies such as Bayesian inferences, exploratory data analysis and resampling. Moreover, it is a common misconception that quantitative research is equivalent to statistical data analysis. As a matter of fact, data analysis is only one of the three components of quantitative research. The other two components are design of experiment and measurement (Pedhazur & Schmelkin,1991).

Eight major themes of logical positivism

Another source of misunderstanding is due to the limited knowledge of positivism among researchers. For clarification, Hacking (1983) made a concise summary of positivism. According to Hacking, there are

six major themes of positivism: (a) an emphasis on verification, (b) pro-observation, (c) anti-cause, (d) downplaying explanation, (e) anti-theoretical entities, (f) anti-metaphysics. Logical positivism accepts all of the above notions and adds the emphasis on logic, meaning, and analysis of language. Based upon the preceding notions, positivists developed a specific version of frequentist probability theory. As a matter of fact, very little resemblance exists between the ideas of logical positivism and that of quantitative research. Each of these positivist ideas will be discussed next.

Verification

According to positivism, a statement is meaningless unless specific conditions are provided for verifying the statement. This notion can be applied in such a radical manner that moral, aesthetic, and religious statements are considered non-verifiable and thus meaningless (Ayer, 1936). Verification is viewed as a property of quantitative research. Quantitative research is said to be deductive in the sense that it begins with pre-determined hypotheses for further verification (Glesne & Peshkin, 1992). The result of this verification is either the truth or falsity of that hypothesis. Thus, quantitative research is said to look for one definite answer (Meehl, 1986). In contrast to verificationism, qualitative research is said to be discovery of new information, which "may reflect new practices or behaviors, new forms of social organization or social structure, and/or new ways of thinking or interpreting processes of socialization or change" (Ambert & Adler, 1995, P.878)

Attributing quantitative research as verificationism has four errors. First, exploratory data analysis (EDA), which is a type of quantitative research method, also emphasizes discovery rather than verification and confirmation. To be specific, EDA is data-driven rather than hypothesis-driven (Behrens, 1997). Tukey (1977, 1980), the founder of the school of EDA, often related EDA to detective work. In EDA, the role of the researcher is to explore the data in as many ways as possible until a plausible "story" of the data emerges.

Second, deduction is not the sole logical foundation of quantitative research. The foundation of hypothesis testing, which is the frequentist view of probability, is inductive in nature. In addition, Yu (1995) Yu, Behrens, and Ohlund (in press) asserts that the logic of EDA rests on neither induction nor

deduction. Rather, abductive logic, which aims to discover a plausible hypothesis, is the underlying logic of EDA. Abduction plays the role of generating new ideas or hypotheses; deduction functions as evaluating the hypotheses; and induction is justifying the hypothesis with empirical data. In other words, abduction, deduction, and induction work together to explore, refine and substantiate research questions.

Third, the result of quantitative data analysis is more accurately viewed as a probabilistic inference rather than a dichotomous answer (true/false) by verification. In statistical testing, a test statistic is extracted out of a finite sample and used to compare against an infinite sampling distribution. The probability (p-value) indicates how likely the result will surface in the long run. Niels Bohr's "Copenhagen interpretation" is well applied to statistical inference though he was in a different discipline. Bohr asserted that one could answer questions of the form: "If the experiment is performed, what are the possible results and their probabilities?" One should not answer any question in this form: "What is really happening when ...?" (cited in Jaynes, 1995, p.1012). For more detail, readers may consult Yu (1999) and Yu, Olhund, DiGangi, & Jannasch-Pennell (2000).

Fourth, the logic of statistical hypothesis testing is not to verify whether the hypothesis is right. Rather, the logic is to find the probability of obtaining the sampled data given the null hypothesis is true. Hypothesis testing is based upon Popper's falsification (Howson & Urbach, 1993; Popper, 1959, 1974). In Popper's view, conclusive verification of hypotheses is not possible, but conclusive falsification is possible. The validity of knowledge is tied to the probability of falsification. The more specific a hypothesis is stated, the higher the possibility that it can be negated.

Popper is explicitly opposed to verificationism (Sanders, 1993). If a theory is claimed to be verified by an observed consequence, the researcher may commit the fallacy of affirming the consequent. A good example of this fallacy is that "if it rains, the floor is wet. If the floor is wet, it rains." In addition, Hacking stated that Popper did not share enough of the major themes of positivist features to be qualified as a positivist. According to Hacking, many features of his theory are contradicted by positivism. For instance, Popper accepted theoretical entities and held that science attempts to discover explanations and causes. He lacked the positivist obsession with observation. Unlike the logical positivists, he thought that a theory

of meaning is detrimental to the philosophy of science. Although one could view his falsification of hypotheses as another version of verification, he accepted untested, metaphysical speculation in the stage of hypothesis formulation. Experienced quantitative researchers could find that Popperian notions, rather than positivist ones, are in alignment to the practice of quantitative research. Taking all preceding incompatibilities into consideration, it can be concluded that positivist verificationism is not a property of quantitative research.

Pro-observation

Positivism has a root in British empiricism (Rice, 1943), and thus, positivism maintained that our sensory impression is the basic source of knowledge. As Schlick (1959) said, reality refers to experience. Empirical observation as a research methodology is not a disputable matter. In one way or another, qualitative researchers observe subjects as empirical input. The debatable issue is the definition of reality as experience. This notion has been inflated as "empirical observation implies one objective reality." To be specific, quantitative research is viewed by qualitative researchers as empirical research that seeks for an objective reality (Glesne & Peshkin, 1992). This is mistaken. There are three points here, sensory inputs as objectivism, statistical models as working models, and subjective probability.

First, based on the assumption that reality refers to experience, one can hardly conclude the existence of an objective reality. Schlick (1959) used a famous example of color perception. When the same person observes two spots of color, he could compare whether the two colors are the same. However, when two different people look at the same colors, it would be impossible to determine that whether their color perceptions are exactly the same. By the same token, when a Likert-scale is presented to two subjects, there is no guarantee that they interpret the terms "very important, "important," "neutral," "unimportant," and "important" in the same way. Measurement errors always exist when the source of knowledge is experience and observation.

Second, quantitative researchers do not necessarily accept an objective reality or believe in the discovery of that reality. Many quantitative researchers view a statistical model as a working model, which is neither right nor wrong. Different researchers could propose different models that are equivalent

or that carry equal explanatory powers. For example, Lord blatantly (1980) dissociated the statistical world and the real world: "A statistician doing an Analysis of Variance does not try to define the model parameters as if they existed in the real world. A statistical model is chosen, expressed in mathematical terms undefined in the real world. The question of whether the real world corresponds to the model is a separate question to be answered as best we can" (p.6).

Third, quantitative research methodology is not necessarily objective. Let alone assuming one objective reality. The Bayesian approach is based upon subjective probability, which represents a degree of belief. Nonetheless, the prior subjective probability would be later corrected by the posterior probability based upon the observed data. In summary, observation as a research methodology is not unique in quantitative methods, and observation does not necessarily lead to the notion of one objective reality.

Anti-cause

Many psychological researchers incorrectly attribute cause and effect to logical positivism. For example, Erlandson et al. (1993) asserted that "the very structure of our language (and thus our conceptual structure?) heavily depends on the traditional term of positivism ... It is particularly hard to expunge from our memories such terms as causality..." (p. xii) By the same token, Nation (1997) states that "one precept of logical positivism is that evidence favoring the objective existence of cause and effect can be provided." (p.68)

Actually, the opposite is true. Positivists asserted that in a strict sense there is no causality. Rather events happen together as a regular association. Russell (1913) explained relationships in terms of functions. For example, $Y = a + bX$ can be rewritten as $X = (Y - a)/b$. Thus, X could not be viewed as a cause of Y because the positions of X and Y could be swapped around the equation. By embracing this equation-oriented notion, Positivist Russell argued against causation, "All philosophers imagine that causation is one of the fundamental axioms of science, yet oddly enough, in advanced sciences, the word 'cause' never occurs... The law of causality, I believe, is a relic of bygone age, surviving, like the monarchy, only because it is erroneously supposed to do no harm." (cited in Pearl, p.337) Pearl, the

renowned computer scientist who defends causality, is objected to Russell's anti-cause attitude, "Fortunately, very few physicists paid attention to Russell's enigma. They continued to write equations in the office and talk cause-effect in the cafeteria; with astonishing success they smashed the atom, invented the transistor and the laser." (p.338)

Obviously, the anti-cause notion is incompatible with quantitative research in the context of randomization experiments, latent construct theory and structural equation modeling. In evaluating the logic of counterfactual, Glymour (1986) said, "One of the principal goals of statistics has always been the determination of causal relations from both experimental and nonexperimental data." (p.966) The cause and effect relationship is still undetermined even if X occurs when Y occurs. An experienced researcher would question whether Y still occurs in spite of Y or regardless of Y. This doubt would lead to a counterfactual question: What would have been happen to X if Y were not present? Some researchers apply randomization experiments in attempt to answer this counterfactual question. By introducing a control group (~X), a causal inference can be asserted based upon the logic of counterfactual: If X is true, then Y is true. If X is not true, Y is not true. Thus, Y is said to be causally responsible for X.

In the latent construct theory, also know as the measurement model, the relationship between the latent factor and the observed item is considered a cause and effect relationship (Borsboom, Mellenbergh, & van Heerden, in press). Although operationalists view the latent construct as nothing more than a numeric trick to simplify the observations (collapsing many observed items into one factor), Borsboom et al assert that operationalism and the latent construct theory are fundamentally incompatible. If a latent construct is just for operational convenience, then there should be a distinct latent factor for every single test researchers construct. However, since it is assumed that observed items that are loaded into a factor constitute a single dimension, theoretical construct are implied to be causally responsible for observed phenomena.

By collapsing observed items into latent constructs, factor analysis is one of the most popular applications of the latent factor theory. Abbott (1998) argued that early psychometricians viewed factor analysis as a mathematical convenience to reduce complex data to simple forms in order to reconcile

quantitative data with intuitive categories, and thus it ignored causality altogether. This view seems to be concurred by Laudan (1977). Laudan classified psychometrics in the early 20th century as "non-standard research tradition" because it does not have a strong ontology and metaphysics. Rather its assumption is "little more than the conviction that mental phenomena could be mathematically represented." (p.105) However, Laudan also asserted that unlike what Thomas Kuhn described in the paradigm theory, a research tradition is hardly static and uniform. Rather competing and incompatible views could coexist within the same research tradition at the same time, and the ontology and metaphysics could change drastically within the tradition over time. Indeed, it is arguable whether early psychometricians were a-causal. While discussing the origin and development of factor analysis, Vincent (1995) asserted that factor analysis is an attempt to identify the causes that are operating to produce the variance, and to evaluate the contribution due to each cause. In his view, the argument among early psychometricians was concerned with whether one common cause or multiple causes were appropriate. Further, modern scholars view factor analysis as an application of the principle of common cause (e.g. Glymour, 1982; Glymour, Scheines, Spirtes, & Kelly, 1987). Factor analysis has been incorporated into the structural equation model, which blatantly allows for causal inferences.

Structural equation modeling (SEM), which entails factor models and structural models, definitely specifies cause and effect relationships (Hoyle, 1995). In SEM, a factor model depicts relationships between indicators and underlying factors (Kline, 1998). Experimental design aims at strengthening causal inferences, which are weak or missing in quasi-experiments and non-experiments (Christensen, 1988; Cook & Campbell, 1979; Luker et al., 1998). Usually SEM requires a very large sample size. It is difficult, but not impossible, to recruit thousands subjects for experimental studies. Not surprisingly, most data in SEM are observational or quasi-experimental rather than experimental. Noneheless, Glymour, Scheines, Spirtes, and Kelly (1987) argued that casual inferences could be drawn from SEM based on non-experimental data. Because after the heuristic algorithm computes thousands of possible ways to fit the data with the model but a unique solution is found, a causal inference is plausible.

Hoyle (1995) asserted that at least three criteria need to be fulfilled to validate a causal inference :

1. Directionality: The independent variable affects the dependent variable.

2. Isolation: Extraneous noise and measurement errors must be isolated from the study so that the observed relationship cannot be explained by something other than the proposed theory.

3. Association: The independent variable and the dependent variable are mathematically correlated.

To establish the direction of variables, the researcher can apply logic (e.g., physical height cannot cause test performance), theory (e.g. collaboration affects group performance), and most powerfully, research design (e.g., other competing explanations are ruled out from the experiment). To meet the criterion of isolation, careful measurement should be implemented to establish validity and reliability, and to reduce measurement errors. In addition, extraneous variance, also known as threats against experimental validity, must be controlled for in the design of experiment. Lastly, statistical methods are used to calculate the mathematical association among variables. However, in spite of a strong mathematical association, the causal inference may not make sense at all if directionality and isolation are not established. In short, all three components of quantitative research, i.e., experimental design, measurement, and statistical analysis, work together to establish the validity of cause and effect inferences. Denying causes would overturn the entire premise of quantitative research. Again, the anti-cause notion of positivism is incompatible with many branches of quantitative methods such as randomization experiments, latent construct theory and structural equation modeling.

Downplaying explanation

It is not surprising that explanation, along with causality, is misidentified as a link between positivism and quantitative research. For instance, Langenbach et al. (1994) asserted that quantitative research, which is based on a positivist philosophy, seeks to explain the cause of changes in social facts. On the contrary, positivists such as Schlick maintain that inquiry of knowledge describes what happens, but does not explain or prescribe it. In Hempel's (1965) view, to explain an event (S), a law (L) is applied and some particular facts (F) are observed to link S and L. This deductive approach is descriptive in nature and thus does not generate any new knowledge. For example,

L: Human behaviors are rational.

F: One of several options is more efficient in achieving the goal.

S: A rational human takes the option, which directs him to achieve his goal (Anderson, 1990).

In this case, "rationality" is the term to describe the phenomenon that humans choose more efficient options. Interestingly enough, the descriptive approach of positivism is more compatible with phenomenological-oriented qualitative research than quantitative research. Quantitative researchers have a different view to explanation. In quantitative research, explanation implies a theoretical formulation about the nature of the relationship among the variables (Pedhazur, 1982). The nature of this relationship may or may not be causal in nature. Within some theoretical frameworks it may be meaningful to compute semipartial correlations, whereas in others, such statistics are not meaningful. In other words, the explanation in quantitative research is not entirely descriptive.

Explanation is tied to statistical modeling. According to Kelley (1998), very often there is a gap between the explanandum (that which is to be explained) and the explanation (hypothesis); a good explanation is capable of bridging the gap. Kelley pointed out that a gap exists in such a simple explanation as "a person is sad (explanandum) because her cat is dead (explanation)." Between the preceding explanandum and the explanation, one must prove that the person is emotionally attached to the cat. In research this gap is even wider, and that is why statistical modeling is necessary. For example, let's evaluate this statement: Children from Protestant families have better performance in school because of the Protestant work ethics. To validate this explanation, many other statements/variables are needed to fill the gap:

X1: Protestant work ethics motivate people to work hard

X2: Working hard accumulates more money

X3: Parents who have more money will buy resources such as books and computers for their child's education

X4: Children who grow up in a Protestant family study harder.

X5: Hard-working children who are exposed to rich educational resources learn better.

Y: Children from Protestant families have better performance in school.

Assuming that we can re-express all of the above statements into measurable variables, a statistical model can be drawn as shown in Figure 1.

Insert Figure 1 about here

In brief, statistical modeling plays a role of filling the gap between the explanandum and the explanation. Quantitative research definitely seeks for explanation and thus does not subscribe to the positivist notion of downplaying explanation.

Anti-theoretical entities

As mentioned before, positivists restrict reality to the observable, reject causal inferences, and downplay explanation. Therefore, positivists are skeptical of unobservable and theoretical entities such as latent variables, or factors. Qualitative researchers drew an association between quantitative research and positivism, which is synonymous with the scientific paradigm. Indeed, positivism is not the modern scientific paradigm because modern scientists have turned away from the positivist position of anti-theoretical entities. A discussion of the existence of nucleus inside an electron by Schlick (1959) is a clear illustration of the positivist perspective to unobservable theoretical entities:

> If someone would say: within every electron there is a nucleus, which, though always present, never has in any way any external effects, so that its existence never manifests itself in nature, this would be a meaningless assertion. For we would have to ask the maker of the hypothesis: what do you mean by the presence of that "nucleus"? And he would answer only: I mean that something exists there in the electron. We would inquire further: what does that mean? What would be the case if it didn't exist? And he would have to answer: everything would remain exactly the same as before. For according to his assertion, the "somewhat" in the electron has no effects, and there would simply be no observable change: the realm of the given would not be affected in any way. We should judge that he had not succeeded in communicating the meaning of his hypothesis, and that therefore it made no sense. (pp. 88-89)

Obviously, the preceding approach hinders scientists from exploring the subatomic world. No wonder Weinberg (1992) argues that the development of 20th century physics was delayed by physicists who took positivism seriously, and thus could not believe in atoms, let alone electrons or smaller particles. Meehl (1986) also pointed out that "it (logical positivism) is not an accurate picture of the structure of advanced sciences, such as physics; and it is grossly inadequate as a reconstruction of empirical history of science." (p. 315)

One example of how modern science advances by going against the notions of pro-observation and anti-theoretical constructs is the development of Heisenberg's uncertainty principle. Once Heisenberg wrote a paper questioning the notion that electrons orbit around the nucleus in an atom. Einstein criticized Heisenberg's narrow view and suggested to him that observations do not drive theories, but theories drive observations. Inspired by Einstein, later Heisenberg developed his famous uncertainty principle (Ferris, 1983).

Newtonian physics is another example that demonstrates the clash between science and positivism. Positivist Ernst Mach regarded Newtonian's notion of absolute space as a figment of the imagination. He argued that without a possible experiment to distinguish absolute motion from relative motion, the term "absolute space" has only metaphysical meaning (Krimsky, 1972). By looking at the above two examples, people who equate science to positivism should have a second thought. Contrary to the popular belief, the advance of modern science heavily relies on theoretical constructs and logical arguments (Kuhn, 1957; Glymour, Scheines, Spirtes, & Kelly, 1987).

As a matter of fact, quantitative research in social sciences asserts abstract theoretical constructs. Campbell (1995) maintained that factor analysis and multi-dimensional scaling must be theory driven. In psychometrics, latent constructs such as self-esteem and intrinsic motivation are always hypothesized. Although Cronbach and Meehl (1955), who developed construct validity, had explicitly accepted the definitional operationalism within the logical positivist framework, construct validity is viewed as a product of a feedback loop between hypothetical, theoretical constructs and observable data. If the notion

of anti-theoretical entities were imposed on quantitative research, a large portion of quantitative research regarding latent constructs would be eliminated. Anti-metaphysics

Positivists deny the existence of metaphysical and transcendental reality (Ayer, 1934; Carnap, 1959). Although both metaphysics and theoretical entities are unobservable, there is a difference between them. In the viewpoint of positivism, theoretical entities such as electronics and self-esteem belong to the physical world. As Schlick (1959) said, the world of science is the same as the world of our everyday life where memories, desires, ideas, stars, clouds, plants and animals exist. In philosophy, the metaphysical world is "the other world" beyond this physical realm. Positivism denies this metaphysical world.

On the other hand, quantitative researchers do not necessarily reject the metaphysical existence. Mathematicians have developed a world of distributions and theorems. Essentially, statistical testing is a comparison between the observed statistic and theoretical distributions. Although statistical methods are considered empirical, Fisher (1956) asserted that theoretical sampling distributions could not be empirically reproduced. Actually, sampling distributions involve not only theoretical entities, but also mathematical reality, which has been a debatable topic in philosophy (Devitt, 1991; Drozdek, & Keagy, 1994; Gonzalez, 1991; Penrose, 1989; Russell, 1919; Tieszen, 1992, 1995; Whitehead & Russell, 1995). Because many mathematicians, statisticians, and quantitative researchers accept the existence of mathematical reality and theoretical distributions, it is obvious that anti-metaphysics is not a property of quantitative methods.

Logical analysis

Logical positivism adds the emphasis of logical analysis of language into positivism. According to Russell's logical atomism (1959), complex phenomena could be expressed in terms of mathematics, and mathematics could be further reduced to logic. By first glance, Russell's notion describes the practice of quantitative research. In quantitative research, events are expressed in terms of numbers and mathematical equations; statistical analysis is viewed as a process of data reduction. However, the link between logical atomism and quantitative methods is questionable when one examines the issue carefully.

There is an inevitable tension between the notion that logic is the foundation of knowledge and the thesis that sensory data is the source of knowledge. This tension is acknowledged by quantitative researchers. Although the previous section mentioned that quantitative researchers embrace theoretical constructs, quantitative research is by no means a one-day reduction from events to numeric data, to mathematical models. Instead, events, data, and theory form a positive feedback loop. For example, when Cronbach and Meehl (1955) proposed the concept of construct validity, they maintained that hypothetical constructs drive the nature of data collection. In turn, the data resulting from the administration of the instrument are then used to revise the theory itself.

Unlike the positive loop in quantitative research, Russell's mathematical model is a formal analysis of a closed system. Russell is not concerned with what the reality is and whether geometric objects exist. The mission of mathematicians is to discover the logical relationships among objects. An axiom is considered valid just because Y logically entails X.

This line of thinking can be found among some quantitative researchers. For example, there is an old saying that "a statistical model is neither right nor wrong." This approach treats a mathematical model as a closed logical system, therefore empirical data does not constitute evidence to prove or disprove a model. Nonetheless, the belief that "all models are false" becomes more popular (Bernardo & Smith, 1994; MacCallum, 1995). In this view, no data can fit any model perfectly and thus all models are wrong to some degree. This saying indicated that quantitative research is an interaction between data and theory, rather than a one-way reduction from events to a logical-mathematical system.

Frequentist probability

Probability theory is considered a specific application of positivism to quantitative methods. Fisherian hypothesis testing is based upon relative frequency in the long run. Since a version of the frequentist view of probability was developed by positivists Reichenbach (1938) and von Mises (1964), the two schools of thoughts seem to share a common thread. However, it is not necessarily true. Both Fisherian and positivist's frequency theory were proposed as an opposition to the classical Laplacean theory of probability. In the Laplacean perspective, probability is deductive, theoretical, and subjective. To be

specific, this probability is subjectively deduced from theoretical principles and assumptions in the absence of objective verification with empirical data. Assume that every member of a set has equal probability to occur (the principle of indifference), probability is treated as a ratio between the desired event and all possible events. This probability, derived from the fairness assumption, is made before any events occur.

Positivists such as Reichenbach and von Mises maintained that a very large number of empirical outcomes should be observed to form a reference class. Probability is the ratio between the frequency of desired outcome and the reference class. Indeed, the empirical probability hardly concurs with the theoretical probability. For example, when a dice is thrown, in theory the probability of the occurrence of number "one" should be 1/6. But even in a million simulations, the actual probability of the occurrence of "one" is not exactly one out of six times. It appears that positivist's frequency theory is more valid than the classical one. However, the usefulness of this actual, finite, relative frequency theory is limited for it is difficult to tell how large the reference class is considered large enough.

Fisher (1930) criticized that Laplace's theory is subjective and incompatible with the inductive nature of science. However, unlike the positivists' empirical based theory, Fisher's is a hypothetical infinite relative frequency theory. In the Fisherian school, various theoretical sampling distributions are constructed as references for comparing the observed. Since Fisher did not mention Reichenbach or von Mises, and vice versa, it is reasonable to believe that Fisher and Reicenhbach developed their frequency theories independently. Salmon (1967), who is a student of Reichenbach, credited Reichenbach as the developer of the frequency theory without a single word about Fisher. Further, backed by a thorough historical research, Hacking (1990) asserted that "to identify frequency theories with the rise of positivism (and thereby badmouth frequencies, since "positivism" has become distasteful) is to forget why frequentism arose when it did, namely when there are a lot of known frequencies." (p.452) In a similar vein, Jones (1999) maintained that "while a positivist may have to be a frequentist, a frequentist does not have to be a positivist."

Discussion

If none of the preceding positivist ideas is linked with quantitative research, why then is positivism perceived as the paradigm of quantitative research? To be fair, there are several links between the two schools of thought in history. For instance, Stevens, the originator of the representation theory of measurement, adopted the ideas of logical positivism and operationalism (Michell, 1997). Cronbach and Meehl (1955), who developed construct validity, accepted operationalism within the positivist framework. One of the most obvious links between positivism and quantitative methods could be found in Karl Pearson. Karl Pearson, the inventor of the correlation coefficient, was a follower of Comte's positivism (Peirce, 1958). According to Pearl (2000), Pearson denied any need for an independent concept of causation beyond correlation. Nevertheless, although Pearson downplayed causal explanation, his view should not be equated with positivists' anti-cause notion. Pearson admitted that correlation analysis might be misleading because of spurious correlation. In other words, behind the two highly correlated variables, there might be other variables acting as common causes. The ultimate objective of research was to find evidence of an "organic relationship," which was "causal or semi-causal." (Aldrich, 1995)

Nevertheless, the development of construct validity has been moving away from operationalism. The modern concept of construct validity is in sharp contrast with operationalism. In operationalism, every term is narrowly defined by a specific set of operations, which becomes its sole empirical referent. In modern construct validity, a measure is taken to be one of an extensive set of indicators of the theoretical construct. In this spirit, multiple items are loaded into a latent factor using factor analysis. Because the sets of indicators are extensible and often probabilistically related to the theoretical construct as well as to each other, constructs are not "operationally" defined, but are more like "open concepts." (Salvucci, Walter, Conley, Fink, & Saba, 1997).

In the early 20th century, positivism was dominant in both natural and social sciences and thus experimental methods were developed under the influence of positivism. However, cultures, including the academic culture, receive influences from multiple sources. For example, several impressionists drew ideas from photography and Japanese printing, yet an art history professor would not stretch to claim that

impressionism is based upon Japanese art or photography. By the same token, the statement that quantitative research is based on positivism ignores the dynamic complexity of the academic culture. Second, the academic culture is evolving. As mentioned in the beginning, philosophers of science have universally rejected positivism. Psychologists have until as recent as the 1960's, based their research on logical positivism (Leahey, 1987). Since many present day psychologists were trained during the 1950's and 1960's, such current beliefs and confusion may be a carryover from that earlier period. Putting a stigma of an out-dated philosophy onto quantitative research may discourage psychological students from learning this research approach, and also lead to misguided dispute between quantitative and qualitative researchers. What is needed is to encourage researchers and students to keep an open mind to different methodologies and apply skepticism to examine their philosophical assumptions instead of unquestioning acceptance.

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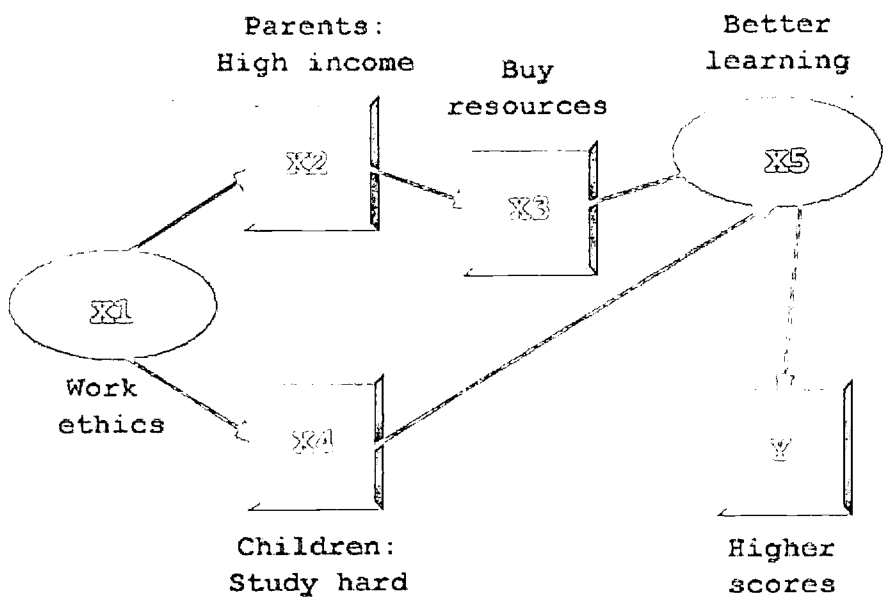
Figure Caption

Figure 1. Relationships between the explanandum and explanation



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